DYNAMIC METHODOLOGIES FOR PROBABILISTIC RISK ASSESSMENT (PRA)

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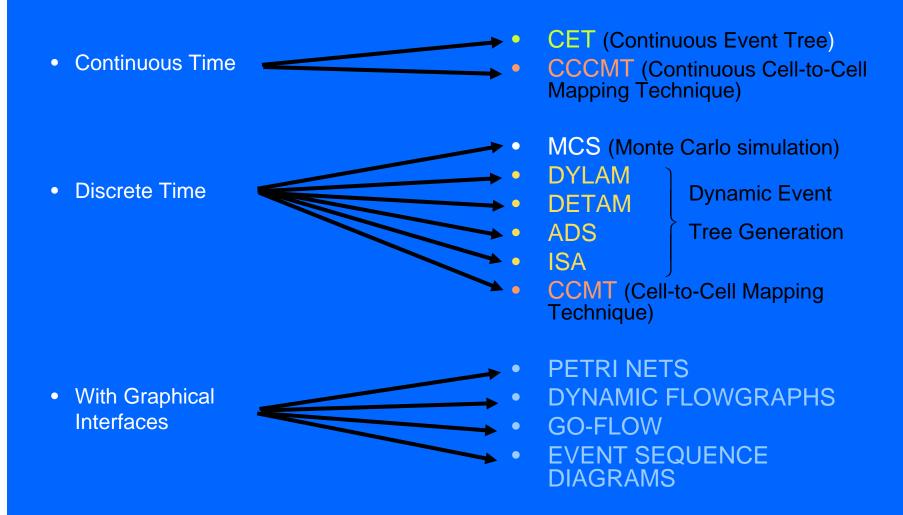
Background

- Conventional approach to probabilistic risk assessment uses the fault-tree/event-tree (FT/ET) methodology
- FT/ET at best can account for the order of occurrence of events in system evolution
- Dynamic methodologies are defined as those that explicitly account for the time element in probabilistic system evolution
- Dynamic methodologies are usually needed when the system has:
 - more than one failure mode,
 - control loops or indirect statistical dependence (coupling) of failure events through the controlled/monitored process (Type I coupling),
 - direct coupling of failure events through hardware/software (Type II coupling),
 - human interaction
- Dynamic methodologies are also expected to be needed for risk informed design of future reactors since uncertainties in model parameters may affect system behavior in a manner similar to component malfunction
- On-line application of dynamic methodologies necessitates identifying the current system state

Dynamic Methods for PRA

- Off-line applications
 - Prognostic methods
- Potential on-line applications
 - Diagnostic methods
 - Prognostic methods

Prognostic Dynamic Methods



Diagnostic Dynamic Methods

Continuous Time
 Adjoint CET

Discrete TimeDSD

Prognostic Dynamic Methods - CET

- Describes the system behavior in terms of the probability π(x,l,t) of finding the system in the state-space (x-space) with configuration i at a given time t.
- Input:
 - System trajectories $g_i(t, x)$ in the state space
 - Configuration transition rates $\lambda_i(x)$ and p(j->i|x)
 - Probability $F_i(t, \mathbf{x})$ that the system leaves configuration i before time t
 - Initial condition $\pi(\mathbf{x}, i, 0)$
- Output:
 - $-\pi(\mathbf{x},i,t)$
- Solution Method:
 - Monte Carlo in the integral form

$$\lambda_{i}(\bar{\mathbf{x}})\pi(\bar{\mathbf{x}},i,t) = \lambda_{i}(\bar{\mathbf{x}}) \int \pi(\bar{\mathbf{u}},i,o) \delta(\bar{\mathbf{x}} - \bar{\mathbf{g}}_{i}(t,\bar{\mathbf{u}})) (1 - F_{i}(t,\bar{\mathbf{u}})) d\bar{\mathbf{u}}$$

$$+ \sum_{j \neq i} \int_{i}^{t} \int \lambda_{j}(\bar{\mathbf{u}})\pi(\bar{\mathbf{u}},j,t-\tau) \left[\frac{\rho(j \to i|\bar{\mathbf{u}})}{\lambda_{j}(\bar{\mathbf{u}})} \right]$$

$$\times \delta(\bar{\mathbf{x}} - \bar{\mathbf{g}}_{i}(\tau,\bar{\mathbf{u}})) dF_{i}(\tau,\bar{\mathbf{u}}) d\bar{\mathbf{u}}$$

If Markov condition holds, i.e.

$$F_i(t,\bar{\mathbf{x}}) = 1 - \exp\left[-\int_0^t \lambda_i[\bar{\mathbf{g}}_i(s,\bar{\mathbf{x}})] ds\right]$$

where $\bar{\mathbf{g}}_i(t,\bar{\mathbf{x}}_o)$ is the solution of the *i*th dynamics

$$\frac{d\bar{\mathbf{x}}}{dt} = \bar{\mathbf{f}}_t(\bar{\mathbf{x}})$$

Then

$$\frac{\partial}{\partial t}\pi(\bar{\mathbf{x}},i,t) + \operatorname{div}(\bar{\mathbf{f}}_i(\bar{\mathbf{x}})\pi(\bar{\mathbf{x}},i,t)) + \lambda_i(\bar{\mathbf{x}})\pi(\bar{\mathbf{x}},i,t)$$

$$-\sum_{j\neq i} p(j \to i|\bar{\mathbf{x}}) \pi(\bar{\mathbf{x}}, j, t) = 0.$$

Prognostic Dynamic Methods - CCCMT

- Describes the system behavior in terms of the probability π_i(j,t) of finding the system in the cell j of the state-space (x-space) with configuration i at a given time t.
- Derivable from CET with

$$\pi_i(j,t) = \int_{j'} dx \ \pi(x,i,t)$$

- Input:
 - Cell-to-cell transition probabilities g(j\j',i',t) in the state space
 - Configuration transition rates h(i|i',x'->x,t)
 - Initial condition $\pi_i(j,0)$
- Output:
 - $\pi_i(j,t)$
- Solution Method:
 - ODE solvers

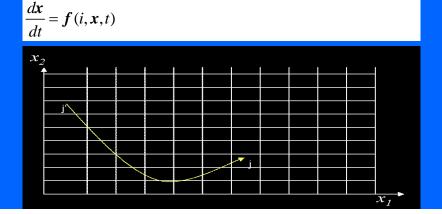
$$\frac{d\pi_{i}(j,t)}{dt} = \sum_{i'} \sum_{j'} \frac{[g(j \mid j',i',t)h(i \mid i',j' \to j,t)\pi_{i'}(j',t) - \lambda(i' \mid i,j',t)\delta_{jj'}\pi_{i}(j',t)]}{-\lambda(i' \mid i,j',t)\delta_{jj'}\pi_{i}(j',t)}$$

$$h(i \mid i',j' \to j,t) = \frac{1}{v_{j'}} \int_{v_{j}} d\mathbf{x}' \int_{j'} d\mathbf{x} h(i \mid i',\mathbf{x}' \to \mathbf{x},t)$$

$$\lambda(i \mid i',j',t) = \frac{1}{v_{j'}} \int_{j'} d\mathbf{x}' \sum_{j} \int_{j} d\mathbf{x} h(i \mid i',\mathbf{x}' \to \mathbf{x},t)$$

$$\frac{1}{v_{j'}} \int_{\hat{\mathbf{n}}(\mathbf{x}_{s}) \cdot f(i',\mathbf{x}_{s},t) > 0} \int_{\mathbf{x}_{s} \in S_{j'}} d\mathbf{x}_{s} \hat{\mathbf{n}}(\mathbf{x}_{s}) \cdot f(i',\mathbf{x}_{s},t) \quad \text{otherwise}$$

$$\frac{1}{v_{j'}} \int_{\hat{\mathbf{n}}(\mathbf{x}_{s}) \cdot f(i',\mathbf{x}_{s},t) > 0} d\mathbf{x}_{s} \hat{\mathbf{n}}(\mathbf{x}_{s}) \cdot f(i',\mathbf{x}_{s},t) \quad \text{otherwise}$$



Prognostic Dynamic Methods - CCMT

- Describes the system behavior in terms of the probability $\pi_i(j,k\tau)$ of finding the system in the cell j of the state-space (x-space) with configuration i at a give time $k\tau$ (k=0,1,...).
- Derivable from CET with

$$\pi_i(j,k\tau) = \int_{k\tau}^{(k+1)\tau} dt \int_{j'} dx \ \pi(x,i,t)$$

- Input:
 - Cell-to-cell transition probabilities g(j\j',l',t) in the state space
 - Configuration transition rates h(i|l',x'->x,t)
 - Initial condition $\pi_i(j,0)$
- Output:
 - $\pi_i(j,k\tau)$
- Solution Method:
 - Matrix solvers

$$\pi_{i}(j,k\tau) = \sum_{i'} \sum_{j'} g_{k-1}(j \mid j',i') h_{k-1}(i \mid i',j' \to j) \pi_{i'}[j',(k-1)\tau]$$

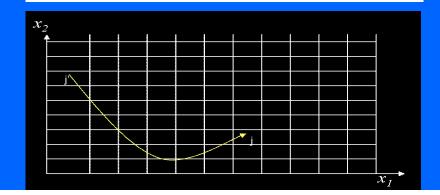
$$h_{k}(i \mid i',j' \to j) = \frac{1}{v_{j'}} \frac{1}{v_{j}} \int_{\tau}^{(k+1)\tau} dt \int_{k\tau} dx \int_{j'} dx \ h(i \mid i',x' \to x,t)$$

$$\begin{cases} \frac{1}{v_{j}} \int_{j'} dx' e_{j} [\widetilde{x}(i',x',k\tau)] & \text{if } j' \text{ is within operating range} \\ 1 & \text{if } j \text{ is a failed state} \\ 0 & \text{otherwise} \end{cases}$$

$$e_{j}(x) = \begin{cases} 1 & \text{if } x \text{ is within } j \\ 0 & \text{otherwise} \end{cases}$$

$$\widetilde{x}(i,x,k\tau) = x[(k-1)\tau] + \int_{(k-1)\tau}^{k\tau} dt \ f[i,x(t),t]$$

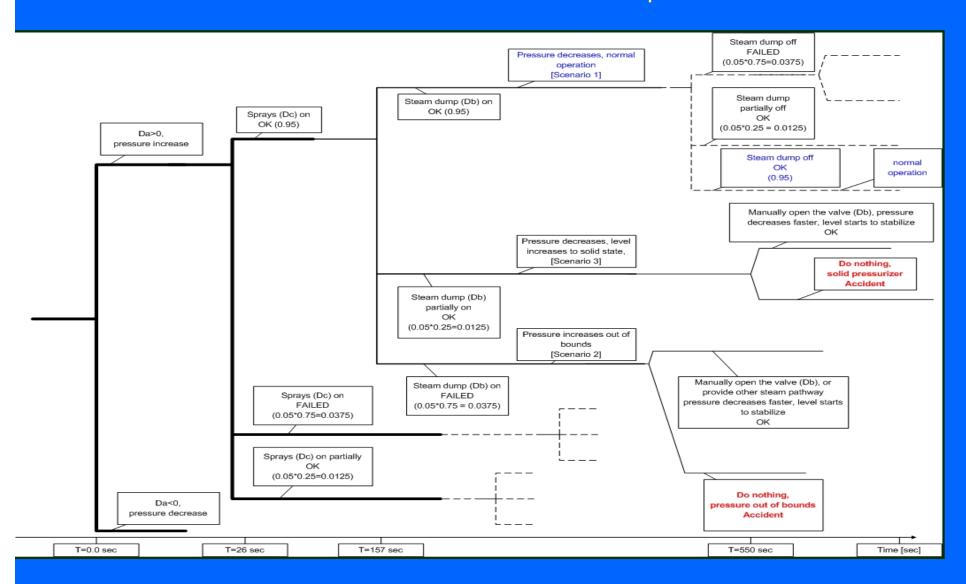
$$\frac{dx}{dt} = f(i,x,t)$$



Prognostic Dynamic Methods – Dynamic Event Trees

- All methods generate event-trees based on possible trajectory branching during system evolution
- Methods differ in terms of branching and pruning rules, human reliability models and operator representation

Part of an ISA Event Tree for an Example Pressurizer



Prognostic DynamicMethods – Graphical

- Usually compatible with fault-trees
- Dynamic variables are represented as nodes of a graph
- Cause-effect relations are represented as the edges of the graph
- Models system evolution in terms of information transmission between nodes

Diagnostic Dynamic Methods – Adjoint CET

• Uses the "backward" Chapman-Kolmogorov equation to find the probability $\pi(\mathbf{x}_0, l_0, t_0 | \mathbf{x}, l, t)$ that the system was at location \mathbf{x}_0 and in configuration i_0 at time t_0 given that it is at location \mathbf{x} with configuration i at a given time t.

Input:

- System equations
- Configuration transition rates $\lambda_i(x)$ and p(j->i|x)
- Initial condition $\pi(\mathbf{x}_0, i_0, 0 | \mathbf{x}, i, t)$ (or data from monitored variables)

• Output:

- $\pi(\mathbf{x}_0, i_0, 0|\mathbf{x}, l, t)$
- Solution Method:
 - Monte Carlo in the integral form

$$\frac{\partial \pi(\boldsymbol{x}_{0}, i_{0}, t_{0} \mid \boldsymbol{x}, i, t)}{\partial t_{0}} + \boldsymbol{f}_{i}(\boldsymbol{x}_{0}, t_{0}) \cdot \nabla_{0} \pi(\boldsymbol{x}_{0}, i_{0}, t_{0} \mid \boldsymbol{x}, i, t) \\
- \lambda_{i_{0}}(\boldsymbol{x}_{0}) \pi(\boldsymbol{x}_{0}, i_{0}, t_{0} \mid \boldsymbol{x}, i, t) \\
+ \sum_{i \neq i_{0}} p(i_{0} \rightarrow i \mid \boldsymbol{x}_{0}) \pi(\boldsymbol{x}_{0}, i_{0}, t_{0} \mid \boldsymbol{x}, i, t) = 0$$

$$\frac{d\mathbf{x}}{dt} = \mathbf{f}_i(\mathbf{x}, t)$$

Diagnostic Dynamic Methods – DSD

• Uses a recursive Bayesian scheme adapted from the prognostic CCMT to determine the pdf $p(j_k|\hat{y}_k)$ of the system location j in the discretized state (or cell) and the configuration space at time $k\tau$ given the observation vector $\hat{y}_k = y_1 y_2 ... y_k$ of observation y_k at each time point $k\tau$ (i.e. data from monitored variables).

• Input:

- Observation y_k at each time point kt
- Probability $p(\mathbf{x}_k|\hat{\mathbf{y}}_k)$ that the system is at location x within a cell at time kτ, given the observation vector $\hat{\mathbf{y}}_k$ (quantifies uncertainty associated with the location of the system within the cell)
- Probability $p(y_k|x_k)$ that the observation is y_k when the system is located at x at time $k\tau$ (quantifies measurement uncertainty)
- Probability $p(x_{k+1}|x_k)$ that the system is at x_{k+1} at time $(k+1)\tau$, given that the system is located at x at time $k\tau$ (quantifies modeling uncertainty)
- Output:
 - $-p(j_k|\hat{y}_k)$
- Solution Method:
 - ODE solvers to determine g(j_{k+1}\vec{j}_k) if the system equations consist of differential equations

$$p(\boldsymbol{j}_{k+1}|\hat{\boldsymbol{y}}_{k+1}) = \frac{\sum_{\boldsymbol{j}_k} g(\boldsymbol{j}_{k+1}|\boldsymbol{j}_k) p(\boldsymbol{j}_k|\hat{\boldsymbol{y}}_k)}{\sum_{\boldsymbol{j}_{k+1}} \sum_{\boldsymbol{j}_k} g(\boldsymbol{j}_{k+1}|\boldsymbol{j}_k) p(\boldsymbol{j}_k|\hat{\boldsymbol{y}}_k)}$$

$$g(\mathbf{j}_{k+1}|\mathbf{j}_{k}) = \iint_{\mathbf{j}_{k+1}\mathbf{j}_{k}} \frac{p(\mathbf{x}_{k}|\hat{\mathbf{y}}_{k})}{\int_{\mathbf{j}_{k}} p(\mathbf{x}_{k}|\hat{\mathbf{y}}_{k}) d\mathbf{x}_{k}} p(\mathbf{y}_{k+1}|\mathbf{x}_{k+1})$$
$$\times p(\mathbf{x}_{k+1}|\mathbf{x}_{k}) d\mathbf{x}_{k} d\mathbf{x}_{k+1}$$

Current Projects at OSU Using Dynamic Methods

- Reliability modeling of digital instrumentation and control systems (NRC)
- Risk-based on-line accident management (SNL)
- Dynamic probabilistic extensions to SAPHIRE (INL)

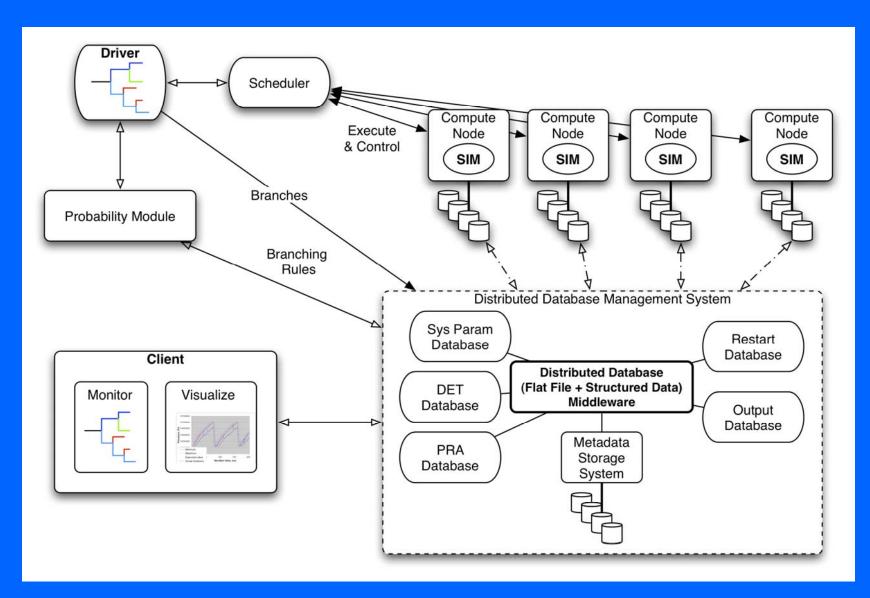
Reliability Modeling of Digital Instrumentation and Control Systems

- An objective is to develop a Markovian methodology for the reliability modeling of digital I&C systems
- Markovian methodology will use CCMT to describe the coupling between the digital I&C system failure events through the controlled/monitored process (Type I) as well as through direct communication and software (Type II)
- The resulting Markov transition matrix will be converted to dynamic event trees for incorporation into existing PRAs

Risk-based On-line Accident Management

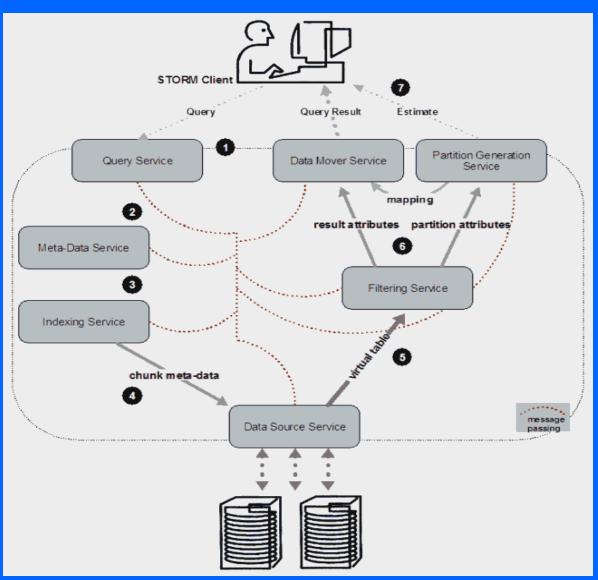
- An objective is to develop system independent software (driver) for mechanized generation of accident progression event trees (APETs) for Level 2 PRA
- Sample system analysis code being used is MELCORE
- Branching rules under consideration for passive components are based on fragility curves
- The driver is being designed for distributed computing
- Uncertainties in process modeling/data will be evaluated by coupling the driver to LHS software developed at SNL

System Architecture



System Architecture Summary

- Scheduler supports multiple execution backends
 - Condor, PBS, ssh/rsh
- Large output files retained on compute nodes
 - accessed by distributed STORM
- Only small files are stored in central database
 - System Parameters:Input files
 - PRA Database
 - DET Database: metadata about simulations



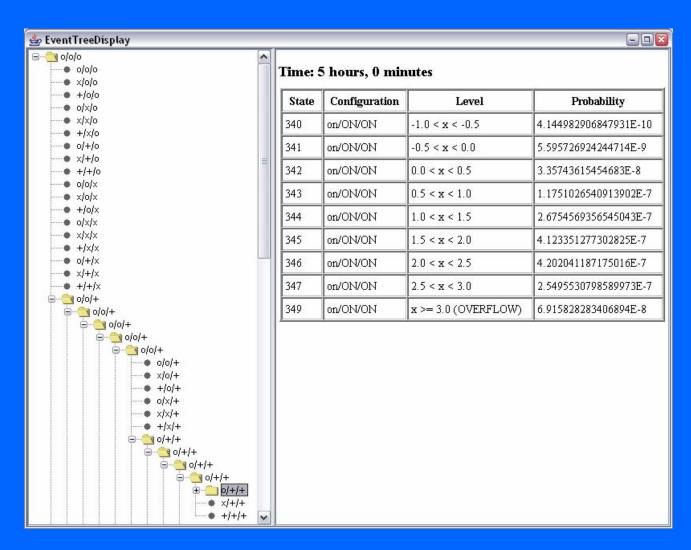
Dynamic Probabilistic Extensions to SAPHIRE

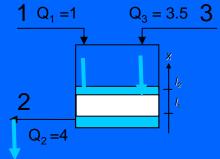
- SAPHIRE is a software tool to perform conventional faulttree/event-tree analysis in a mechanized manner
- The project objective is to extend the applicability of SAPHIRE to systems where Type I and Type II coupling of failure events may be important
- An option to accomplish this objective is to develop modules on the SAPHIRE platform which can:

 – generate Markov models using CCMT, and,

 - convert the Markov model into dynamic event trees.

A Sample Dynamic Event Tree Generated from A Markov Model for a Simple Level Control System





Normal operation

- If Unit 1 fails stuck when x<l₁, system fails by dryout
- •If Unit 1 fails stuck when $x>l_2$ system fails by overflow

Conclusion

- Dynamic methodologies may be needed for PRA of systems with Type I and/or Type II coupling between failure events
- Dynamic methodologies are also useful for risk informed design/management of Generation IV reactors
- Dynamic methodologies may demand substantial computational resources
- Most dynamic methodologies are suitable for distributed computing

